Empirical Quantification and Prediction of Building Component Lifespans with Graph Neural Networks

Author(s):
Wu, Pei-Yu; Mundt-Petersen, S. Olof

Publication date:
2025

Permanent link:
https://doi.org/https://doi.org/10.3929/ethz-b-000742857

Empirical Quantification and Prediction of Building Component Lifespans with Graph Neural Networks

Pei-Yu Wu[1*] and S. Olof Mundt-Petersen [2,3]

[1] Institute of Construction and Infrastructure Management, ETH Zurich, Switzerland
[2] Department of Building and Environmental Technology, Lund University, Sweden
[3] The Swedish Federation of Wood and Furniture Industry, Sweden

[*]E-mail: pei-yu.wu@ai.ethz.ch

Abstract. Extending the service life of existing buildings and their components is essential for slowing resource loops in circular construction. While overall building lifespans are relatively well understood, the actual service lives of individual components remain underexplored due to limited empirical data. This study addresses this gap by analyzing and modeling building component lifespans using real-world damage investigation records and condition assessments from Swedish buildings. Descriptive statistics reveal a wide range of lifespans across six major component categories, highlighting materials linked to damage from poorly designed construction details as a critical factor. Additionally, most residential components have markedly shorter lifespans-about 25–30 years-compared to non-residential ones. To predict component service lifespans, we configure building envelope deterioration factors as a generic acyclic graph and employ Graph Neural Networks for node-level regression. Among the tested models, Graph Convolutional Network achieved the highest performance (R^2 = 0.83), outperforming GraphSAGE and Graph Attention Network due to its effective uniform aggregation across neighboring nodes. Our findings provide a high-granular, data-driven approach to estimating component lifespans, which can enhance predictive maintenance strategies and optimize the reuse potential of reclaimed materials in their next lifecycles.

1. Introduction

Accurately estimating the service life of building components is essential for preventive maintenance and assessing their reuse potential. Such kind of in-time adaptive intervention is particularly of interest for historic buildings to maintain non-renewable heritage values from original materials that is otherwise vulnerable to climate change [1]. Besides, extending the lifespans of most primary building components, aside from windows and rooflights, can significantly reduce environmental impacts [2]. However, static "design or reference lifetimes" often fail to reflect real-world conditions due to external factors such as environmental conditions, operational use, and construction methods [1]. International standards, i.e., ISO 15686-1 [3], and statistical approaches attempt to address this complexity by estimating “dynamic lifetimes” through heuristic calculations or experiments for specific components or materials. Yet, these estimates in controlled environments often differ from actual service life in real-world conditions, a discrepancy that has received limited attention due to a lack of empirical data. Emerging high-resolution data from building status inventories can help quantify these

deviations as deterioration rates, factoring in various influences. Combined with advancements in machine learning, this data opens new possibilities for validating and refining component lifetime predictions.

1.1 State-of-the-art

Methods for lifespan estimation

Statistical approaches and the factor method are commonly used to predict the lifespan of building components under varying conditions. Statistical models are effective for analyzing and predicting fatigue life in situ materials but are primarily focused on preventing fatigue failures in engineering structures. For example, Kracík & Strnadel [4] demonstrated that mixture models of log-normal components outperformed Gaussian mixture models in predicting the probabilistic distribution of random loading cycles for steel structures using experimental data. In contrast, the factor method is more widely used for service life planning of buildings and constructed assets. It is a standardized approach, defined in ISO 15686-1 [3] that takes component lifecycles and states into account, as outlined in Eq. (1):

$$\text{ESL} = \text{RSL} * f_A * f_B * f_C * f_D * f_E * f_F * f_G \quad (1)$$

The Estimated Service Life (ESL) of building components is calculated by applying seven factors to their Reference Service Life (RSL). These factors include inherent quality characteristics, such as material performance (f_A), design level (f_B), execution level (f_C); environment conditions, including interior (f_D) and exterior (f_E) environments; and operation conditions, such as in-use conditions (f_F) and maintenance level (f_G). Each factor is calibrated based on observed anomalies, quantified numerically and visually using a graphical method that accounts for their causes, severity, and extent [5]. Verification of ESL predictions against literature and empirical data has proven robust and accurate. For instance, Jardim et al. [5] used the factor method to predict the service life of architectural concrete surfaces undergoing natural degradation. They examined aesthetic anomalies (e.g., dirt, moisture, and corrosion stains), mechanical anomalies (e.g., disaggregation, oriented or mapped cracks), and construction anomalies (e.g., flatness defects, dribbling, honeycombing). The subfactors were selected based on material-specific contexts, considering data availability from field surveys and relevance, and classified into binary or multi-class states. Different scenarios were created to perform durability subfactor quantification (k), of which the optimal combination of k values minimized the deviation between ESL predictions from the factor method and the graphical method (values observed in fieldwork).

Several studies employ the factor method with relevant component-specific subfactors for the durability assessment of concrete surface, exterior cladding, and window frame etc., summarized in Table 1. Loli et al. [1] applied to predict the exterior cladding deterioration of cultural heritage wood and masonry buildings under varying distributions of factor values (normal, deterministic, and log-normal) for three percentile values (5%, 50%, and 95%) across recent past and future climate change scenarios. In addition to the strong influence of indoor and outdoor climates, they identified building usage, ownership type, and budget constraints for maintenance or renovation as key parameters affecting the Estimated Service Life (ESL). Similarly, Maia et al. [6] used durability factors to optimize a model for predicting service life changes in window frames. The factor method offers a practical approach for identifying component groups with varying lifecycles of maintenance interventions and building life-cycle costs at the district level. However, uncertainties in factor determination and potential interdependencies could

benefit from multidisciplinary expert input, experiments, and detailed analysis [1]. Despite its utility, the method demands significant effort to gather comprehensive data for each subfactor and its associated attributes on a case-by-case basis, limiting its scalability to urban contexts or other geographical regions. Additionally, it combines "technical, measurable, and quantitative" parameters with "human-related qualitative" factors, creating ambiguity in how these subfactors should be weighted and assessed in a standardized manner.

Table 1. Deterioration assessment of in situ building elements using the factor method.

Component	Relevant subfactors for durability calculation	Reference
Concrete surface	surface color (f_{A1}), surface treatment (f_{A2}), finishing type (f_{B1}), surface orientation(f_{E1}), distance from the sea (f_{E2}), exposure to damp conditions (f_{E3}), surface's level of protection(f_{E4}), exposure to wind-driven rain (f_{E5}), ease of inspection (f_{G1})	Jardim et al. (2019) [5]
Exterior cladding*&**	quality of original material (f_{A1}), quality of later material (f_{A2}), quality of treatment (f_{A3}), design technique (f_{B1}), sheltering (f_{B2}), decoration (f_{B3}), energy requirements (f_{B4}), level of workmanship (f_{c1}), temperature (f_{D1}), relative humidity (f_{D2}), mold (f_{D3}), time of wetness (f_{E1}), dry days index (f_{E2}), frost days index (f_{E3}), heavy precipitation index (f_{E4}), tropical night index (f_{E5}), type of use (f_{F1}), flux of use (f_{F2}), surrounding activities (f_{F3}), ease of maintenance (f_{G1}), ownership type (f_{G2}), budget limitations (f_{G3})	Loli et al. (2020) [1]
Window frame	coating type (f_{A1}), window glazing (f_{B1}), shading condition (f_{B2}), exposure to water vapor (f_{D1}), orientation (f_{E1}), exposure to wind-driven rain (f_{E2}), distance from the sea (f_{E3}), exposure to pollutants (f_{E4}), regular maintenance (f_{G1})	Maia et al. (2020) [6]

* Additional environment subfactors apply to masonry building: freezing-thawing cycles (f_{D4}), salt crystallisation cycles (f_{D5}), thenardite-mirabilite cycles (f_{D6}), time of wetness (f_{D7}), freezing-thawing cycles (f_{E6}), salt crystallization cycles (f_{E7}), wet days index (f_{E8}).
** Additional environment subfactors apply to wood building (W): insects (f_{D8}).

Component or material service lifespans in Swedish buildings

A basic information on building elements or materials lifespans are available for Swedish buildings, however, they are based on expert assumptions of property status evaluation without construction details and building types. Therefore, these are regarded as reference values and cannot be used to infer remaining lifespan of the building elements. In public buildings, it is estimated that frame can last up to 100 years, following by supply and drainage system for 40 years, façade and fire extinguish system for 30 years, roof, window and electrical system for 25 years, foundation and heating, ventilation, and air conditioning (HVAC) systems for 20 years [7], these estimations are uncertain and vary according to material types, i.e., cement or ceramic materials, and constructed specification, i.e., depths, reinforcement, treatment, base materials. Detailed lifespan ranges for each material category, including cement and lime-bound materials, ceramic materials, metal materials, wood-based materials, glass, plastic and joint materials, surface materials, and roof materials, along with their construction types are described by Burström [8] with 3 to 25 years standard deviation.

1.2 Research scope

Status and damage inspection in building operational stage by experts presents a new potential for evaluating actual component lifespans from empirical data. It contains damages identified in various types of existing buildings encompassing details on damage specifications, building characteristics, and situated environment, providing extensive contextual subfactors to conduct backward induction of k values in the factor method for predicting comprehensive building components in heterogeneous building stock. The study aims to investigate such possibility by preprocess damage observations and modelling them with the state-of-the-art graph neural network method. The research objectives are to (i) identify damage-specific deterioration factors from clusters of damaged components, and then (ii) visualize and estimate the lifespan distribution of damaged components. The study addresses the scalability and uncertainty limitations of the factor method by contributing to a heuristic and unified approach to examine actual lifetime of components from available damage inspection records.

2 Methods

2.1 Dataset

This dataset comprises of 2,100 complex moisture damage records from 428 real damage investigations or status inventories from school buildings (44%), multi-family houses (24%), single-family houses (19%) and non-residential buildings (14%), referred to our previous study [9]. These investigations conducted by accredited damage inspectors between 2014 and 2021 in the middle and southern regions of Sweden. The dataset includes complex damage investigations with quantitative measurable parameters and excludes simpler issues, such as free water leaks (damages cause by defects in pipes and waterproof membranes), which could be resolved on-site or by moisture technicians and have been investigated by Swedish Water Damage Center [10].

Ten primary damage types of microbial growth, deformation, odor, water leakage, rot, dirt, elevated humidity, poor thermal comfort, condensation, and damp rose were identified across several types of damage elements or components, labelled multiple times in the inspected buildings. The distributions of the damage components are outer wall (33%), floor (15%), indoor environment (12%), floor beam (10%), inner wall (7%), inner roof (6%), roof (4%), door and windows (4%), foundation (4%), installation (2%), interior (2%), structure (1%). Around half of damaged components are located in rooms or classrooms, 10% in balcony or terrace, 9% in basements, 7% in bathrooms, 6% in attics, 6% in kitchen and dining rooms, and the rest in commercial space, corridor, storage, crawl space etc.

2.2 Data preprocessing

To have sufficient number of observations per target components, they were grouped into six labels, namely, outer and inner walls (N=763), floor including beams (N=465), indoor environment and interior (N=271), roof including inner roof (N=204), door and windows (N=82), foundation and structure (N=57). Observations with extreme lifespans, including those larger than 95 years or smaller than 5 years were removed as they do not reflect the actual lifespans from empirical perspective (Offentliga Fastigheter, 2018). Thereafter, statistical analyses were conducted for each component subgroup to compute the average lifespan and the confidence intervals for the combined variables of materials and damaged types, represented in line charts and overlay with error bars. The distribution of individual observations for the combined variables was also visualized in split violin plats and swarm plots for further comparison with reported component lifespans in the Swedish literature.

The estimated service life of a building component depends on both local factors (e.g., material performance) and broader environmental or operational contexts. Relevant subfactors

influencing the lifespan of walls and roofs were identified from the dataset. These subfactors could be categorized into environment (e.g., climate zone, vulnerability to wind-driven rain), building characteristics (e.g., building type, ownership type), and construction details (e.g., facade, wall, roof, roof slope, length of roof overhang) related variables. The core compoent properties are described by lifespan, material and damage tpyes of building compoents. Based on knowledge and experience of building damage experts on the causal relationships of these subfactors, a directed acyclic graph (DAG) was constructed explicitly as graph reprenstaion of the dataset by transforming these subfactors into nodes. Then the dependencies between building components are represented in a DAG using three types of edges indicate relationship types between nodes: ← (*affect*), – (*associate*), and → (*attribute*), as shown in Figure 1.

Figure 1. Proposed directed acyclic graph for service lifespan of building envelope based on expert assumptions of building inspectors. The color annotation of the nodes refers to building component (purple), environment (blue), building characteristics (yellow), and construction details (red).

The *affect* type denotes a causal relationship, the *associate* type suggests a connection without a clear directional link, and the *attribute* type signifies characteristic belonging. For example, the lifespan of components is affected by damage type and associated with component type and material use, denoted as (lifespan ← damage type, lifespan – component & material). Drawing from the relevant moisture damage literature [11–13], the relationships among other nodes in the DAG are as follows: (component ← vulnerability to wind-driven rain, component → building type & material, component – lifespan); (material ← vulnerability to wind-driven rain, material → component, material – lifespan, damage type); (damage type ← vulnerability to wind-

driven rain, damage type – material & climate zone & building type); (roof → roof slope, roof – climate zone & ownership); (roof slope ← climate zone); (roof overhang ← vulnerability to wind-driven rain); (facade ← vulnerability to wind-driven rain, facade → building type & ownership, facade – climate zone & roof overhang & wall); (wall ← vulnerability to wind-driven rain, wall → building type, wall – roof overhang & facade); (vulnerability to wind-driven rain – climate zone); (climate zone – vulnerability to wind-driven rain & damage type & roof & facade); (ownership – building type & facade & roof); and (building type → roof & facade & wall, building type – ownership type & component & damage type). However, the exact magnitude of these effects is unknown, and as such, the edges in the DAG are unweighted.

2.3 Graph neural network modeling

The predefined graph in Figure 1 served as the basis for constructing the PyTorch Geometric (PyG)'s data object, a specialized library for developing Graph Neural Networks (GNNs) from structural tabular data. GNNs were chosen for their ability to model relational structures, aggregate information from neighboring nodes, and flexibly adapt to different component subsets [14]. Given the small dataset (1,500 nodes), shallow GNN architectures (1–2 hidden layers) were employed to progressively extract and abstract features, mitigating overfitting and oversmoothing in node classification tasks for graph-based tabular learning with known, limited relationships [15]. The regression tasks aim to predict the node feature "lifespan" by leveraging relationships among 12 categorical node features (roof slope values are pre-categorized into intervals in the raw dataset). The dataset was split into 70% training, 15% validation, and 15% testing subsets. To compare performance, three GNN architectures were implemented: a shallow Graph Convolutional Network (GCN), a shallow Graph Sample and Aggregation Network (GraphSAGE), and a shallow Graph Attention Network (GAT). GCN captures structural and feature-based relationships but assigns equal importance to all neighboring nodes. In contrast, GraphSAGE samples a fixed number of neighbors, improving scalability for large graphs. GAT further enhances this by incorporating self-attention, allowing the model to dynamically weigh each neighbor's relevance for heterogeneous graphs where node significance varies.

To prevent excessive feature compression during training, the network utilized an input layer of 12 features. A dedicated embedding layer encoded categorical variables, which were then concatenated with numerical features. The first hidden layer expanded the feature space using ReLU activation to model non-linear relationships and mitigate gradient shrinkage during backpropagation, optimized via Adam. The second hidden layer reduced dimensionality for high-level abstraction. The output layer applied ReLU followed by a sigmoid function to produce lifespan probability estimates within a 100-year range. Model performance was evaluated with mean squared error (MSE) as the loss function to minimize the difference between training and validation subsets. Afterwards, R-squared (R^2), a metric that measures the proportion of variance in the dependent variable explained by the independent variables, was used to assess whether the model captures meaningful relationships beyond random noise in the validation dataset.

3 Results and analysis

3.1 Service lifespan distributions in building components from descriptive analysis

Figure 2 presents the quartile-based lifespan distributions of building components in residential and non-residential buildings, ordered by descending sample size. Most residential components exhibit significantly shorter lifespans—around 25–30 years—than their non-residential counterparts. Notable exceptions are the indoor environment, roof, and foundation, which show similar or even longer median lifespans in residential settings. Such difference between building

categories for may be due to “professional management” compared to management by private persons. Moreover, residential components generally have wider interquartile ranges, indicating greater variability. In contrast, the median lifespans of the building envelope, floors, foundations, and installations are nearly identical across both building types, all exceeding 40 years. The same lifespan tendency for exterior walls, and doors and windows are deemed to be logical since they are in building façade.

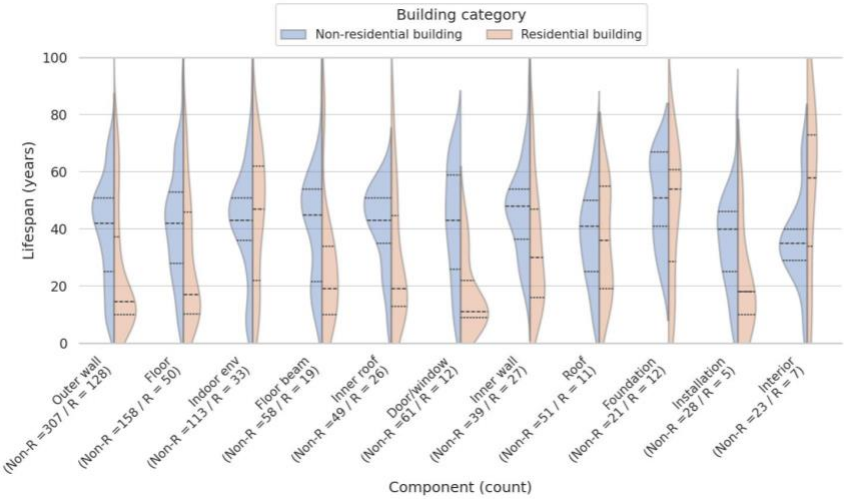

Figure 2. Quartile distributions of building component lifespan by building category. Residential building is color-coded in orange and non-residential buildings in blue.

Additionally, Figure 3 illustrates the mean lifespan and standard deviation across six building component categories, taking into account both material types and damage characteristics. The average service lifespans of all components range from 20 to 60 years. Components with shorter lifespans, such as deformed floor tiles and flaking paint in the inner roof, fall toward the lower end of this range, while components such as deformed concrete foundations or structures represent the higher range. For individual components, the standard deviation of lifespan varies significantly, with most components falling within the 30 to 40 year range. The swarm plots further illustrate a uniform distribution of lifespans for gypsum board walls damaged by mold and deformed plaster walls, deformed linoleum floors, and windows or doors affected by mold. In some cases, lifespan observations reveal distinct lower and upper limits, with certain components failing in less than 20 years or lasting more than 40 years. Early damage is often the result of faulty construction design, while later damage may be attributed to maintenance practices or components simply reaching the end of their service life. Examples include mold-affected wooden studs or sills in interior walls, mold-damaged wood panels in inner roofs, and persistent interior odors caused by damaged windows or doors-often due to missing air gaps in wooden exterior walls.

3.2 Predictive modeling for estimating component lifespan

Table 2 compares the performance and hyperparameter settings of three GNN models—GCN, GraphSAGE, and GAT—for a regression task. GCN achieves the highest R^2 score (0.83), followed by GraphSAGE (0.73), while GAT struggles with a significantly lower score (0.35). A high R^2 indicates the models is capable of explaining overall varaince and capture boradly lifespan trends, even if specific components (e.g., interior walls) have large errors due to unmeasured factors like hidden moisture damage. The results suggest that GCN is best suited for this dataset, likely due to its simple but effective message-passing mechanism. GraphSAGE, though slightly weaker, still

performs reasonably well, possibly due to its sampling-based aggregation. GAT's poor performance may indicate that attention-based mechanisms are not well-aligned with the dataset's structure or that its hyperparameters need further tuning.

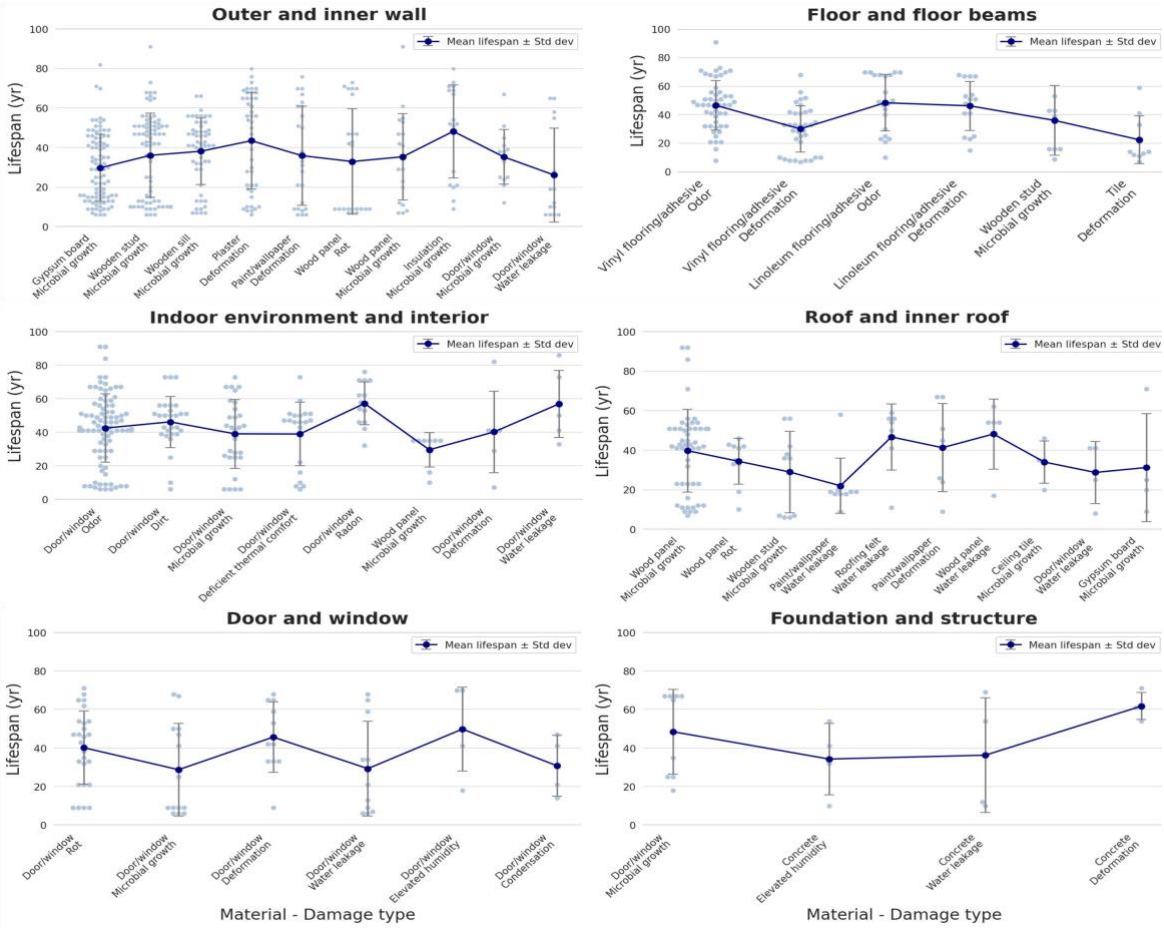

Figure 3. Lifespan distributions of building components by material and damage types.

Table 2. Comparison of performance and hyperparameter combination between GNN model types.

Performance	GCN	GraphSAGE	GAT
R-squared	0.83	0.73	0.35
Embedding dimension	64	80	48
Hidden dimension	32	24	40
Epoch	250	250	250
Learning rate	0.001	0.001	0.001

4 Discussion

4.1 Result implications

The fact that damage occurs as a result of cause of damage and subsequent causing damage can occur over a large period of time is probably what explains the large spread in many results.

However, it is very interesting that the spread varies considerably for different materials and building components etc. The results presented in Figure 2 were compared with material lifespan estimates from the reviewed literature for verification. Overall, the service lifespans of building components are generally shorter with a larger standard variation than those reported in the literature for most investigated materials. For reinforced concrete used in building structures and foundations, components with a lower water-cement ratio (which has been standardized in Swedish buildings since around 1995) exhibit a lifespan of approximately 75±25 years, which is slightly longer than concrete affected by deformation (60±10 years), water leakage (38±35 years), or elevated humidity (35±20 years) in Swedish buildings [8]. Deformed plaster on exterior or interior walls has a service life of 45±25 years, closely aligning with Burström's [8] finding for lime plaster (45±15 years) and Jardim et al.'s [5] estimate of 45±3 years using the factor method.

Wood-based windows and doors were found to last 40±20 years before showing signs of rot, 30±20 years before mold growth, and 45±20 years before deformation. These findings are relatively consistent with Burström [8] (40±10 years) but exceed the 28-year estimate reported by Maia et al. [6]. The lifespan of wood panels remains relatively consistent across different components but varies depending on the type of damage. Rotten or mold-affected wood panels on exterior and interior walls last 30±30 years and 35±25 years, respectively, similar to rotten (35±10 years) and mold-affected (40±20 years) wood panels on roofs or inner roofs. However, water leakage becomes a significant issue after 50±20 years. Additionally, paints and wallpapers exhibit a shorter lifespan when exposed to water leakage (23±15 years), while deformation-free surfaces last significantly longer (40±24 years) on walls or roofs. This aligns with Burström's [8] findings, where cement paint on plaster has a lifespan of 25±5 years, and factory-painted aluminium sheets last 40±10 years.

4.2 Limitations and future research

The dataset's primary limitation lies in its inclusion of only 2% undamaged buildings. Consequently, building components could achieve longer service lives if not compromised by faults or damage. Furthermore, the lifespan of damaged components remains inherently uncertain, as calculations rely on the period between construction and damage identification. In many cases, components may have been deteriorating long before visible issues prompted inspection. However, damages are sometimes detected precisely during routine status inventories, which are more frequent in public buildings (e.g., schools, municipally owned housing). Future studies could prioritize this segment to refine lifespan assessments and enhance preventive maintenance strategies.

A key limitation in further reducing loss and improving GNN models tailored to different component subsets is dataset size. While the current dataset includes 1,500 buildings for this node regression task, an ideal dataset size would range from 2,000 to 5,000 observations. To address this, future research could explore various data augmentation strategies, such as modifying graph construction (e.g., increasing graph connectivity using *k*-nearest neighbours based on categorical embeddings), enhancing categorical feature diversity (e.g., synthetic category sampling with synthetic minority over-sampling technique for nominal and continuous variables (SMOTE-NC)), or generating synthetic data using generative models (e.g., variational autoencoders (VAE) for tabular data or tabular generative adversarial network (Tabular GAN)). Additionally, model optimization can be further improved through a hyperparameter grid search by applying *ParameterGrid* from the scikit-learn's library to explore different combinations of hidden dimensions, embedding dimensions, learning rate, and epochs. To prevent

overfitting, dropout and early stopping are applied between layers. Model performance is assessed using k-fold cross-validation to ensure robust evaluation.

5 Conclusion

This paper investigates the service lifespan of building components affected by moisture damage across the middle and southern regions of Sweden. Descriptive statistics and data visualization confirm most residential components exhibit shorter lifespans (~25–30 years) compared to non-residential counterparts, except for the indoor environment, roof, and foundation. A broad distribution of lifespans is also observed across six major component categories: exterior and interior walls, floors and floor beams, interiors, roofs and inner roofs, doors and windows, and foundation and structure. Our findings suggest that lifespan variations are more strongly influenced by material and damage type than by component category. The predictive analysis demonstrates the potential of GNNs for estimating component service lifespan, with the GCN achieving the highest performance (R^2 = 0.83). GCN's uniform aggregation across neighboring nodes appears well-suited for the given dataset, which remains relatively small. In contrast, GraphSAGE and a shallow GAT, which are designed for heterogeneous and dynamic graphs, were less effective. To the best of the author's knowledge, this is the first study applying GNNs to predict building component service lifespans, highlighting a promising direction for future research in predictive maintenance and lifecycle assessment.

Acknowledgements

This research was supported by ETH AI Center, with data from Polygon Group and input from the Moisture-Proof Wooden Buildings in Sweden project steering and reference groups.

References

1. Loli A, Bertolin C, Kotova L (2020) Service life prediction of building components in the times of climate change. IOP Conf Ser Mater Sci Eng. https://doi.org/10.1088/1757-899X/949/1/012048
2. Marsh R (2017) Building lifespan: effect on the environmental impact of building components in a Danish perspective. Architectural Engineering and Design Management 13:80–100
3. International Organization for Standardization (2011) ISO 15686-1:2011(en), Buildings and constructed assets — Service life planning. In: International Organization for Standardization.
4. Kracík J, Strnadel B (2018) A statistical model for lifespan prediction of large steel structures. Eng Struct 176:20–27
5. Jardim A, Silva A, de Brito J (2019) Application of the factor method to the service life prediction of architectural concrete. Canadian Journal of Civil Engineering 46:1054–1062
6. Maia M, Morais R, Silva A (2020) Application of the factor method to the service life prediction of window frames. Eng Fail Anal.
7. Offentliga Fastigheter (2018) Statusbedömning av fastigheter.
8. Burström PG (1999) Livslängdsbedömningar av byggnadsmaterial.
9. Wu PY, Johansson T, Mundt-Petersen SO, Mjörnell K (2024) Predictive modeling and estimation of moisture damages in Swedish buildings: A machine learning approach. Sustain Cities Soc.
10. Swedish Water Damage Center (2024) Vattenskador i Sverige 2023.
11. Mundt-Petersen SO, Wallentén P, Edskär IJ, Joelsson KOA (2023) Causes of Damages in Swedish Buildings. In: XVI International Conference on Durability of Building Materials and Components. Beijing, pp 1–10
12. Wu P-Y, Johansson T, Mundt-Petersen SO, Mjörnell K (2024) Probabilistic distributions of moisture damages in Swedish buildings. International Building Physics Conference
13. Wallentén P, Mundt-petersen SO, Joelsson KOA, Kläth M (2023) Damaged Swedish Buildings. In: XVI International Conference on Durability of Building Materials and Components. Beijing, pp 1–10
14. Han J, Cen J, Wu L, et al (2024) A Survey of Geometric Graph Neural Networks: Data Structures, Models and Applications.
15. Wu F, Zhang T, Holanda De Souza A, Fifty C, Yu T, Weinberger KQ (2019) Simplifying Graph Convolutional Networks. International Conference on Machine Learning (ICML)